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Variations in breathing patterns increase low frequency contents in HRV spectra

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Abstract. This paper shows that variations in breathing patterns broaden heart rate variability (HRV) spectral bands and increase the power amplitude of low-frequency bands. Because of these influences, spectral markers for HRV signals, such as the quotient between spectral power at different frequency bands, should be compared only under controlled breathing conditions or after considering the effect of variations in breathing patterns.

Keywords: heart rate variability, spectral analysis, respiratory sinus arrhythmia, controlled respiration

1. Introduction

Heart rate variability (HRV) analysis has become a useful tool to study the relationship between the autonomic nervous system (ANS) and the cardiovascular system (CS). HRV is usually studied from the RR time series, either by time-domain methods (Kleiger *et al* 1993), nonlinear dynamics (Wada *et al* 1993), or spectral analysis (Pagani *et al* 1986). HRV analysis has been applied, for example, to study the risk of cardiac electrical instability after myocardial infarction (Bigger *et al* 1991), to diagnose diabetic neuropathy (Pagani *et al* 1988), to assess re-innervation after cardiac transplantation (Sands *et al* 1989) and to evaluate exercise training (Arai *et al* 1989).

Spectral analysis describes the frequency distribution of signal power. Analysis of rhythmic events in the RR time series permits us to infer the state of biological oscillators that modulate the CS, the sympathetic and vagal efferent activity, humoral factors and the sinus node (Task Force 1996). Usually, the power spectrum of the RR time series is divided into three bands: the very-low-frequency (VLF) band, the low-frequency (LF) band, and the high-frequency (HF) band. Vagal activity is the major contributor to the HF component mostly because of the respiratory sinus arrhythmia (Pomeranz *et al* 1985). The LF band is assumed to reflect sympathetic modulations or both sympathetic and vagal activity. In HRV spectral analysis, the biological oscillators that modulate the CS are commonly considered to remain invariable. Nevertheless, the amplitude and frequency of that modulation is seldom stationary in practice.

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This work investigates the effects of breathing-frequency variations in the spectral quantification of HRV signals. Respiratory activity causes a modulation in RR time series at the breathing frequency, which is termed respiratory sinus arrhythmia. The amplitude of this modulation depends on vagal tone (Kollai and Mizsei 1990) and on the breathing frequency itself (Womack 1971) (high breathing frequencies yield smaller amplitude oscillations in the RR spectrum than low breathing frequencies). Hence, changes in breathing frequency should be reflected in the RR time series as a modulation in both amplitude and frequency, and result in a modified spectrum of the RR time series as compared to that obtained during periodic breathing. Consequently, we can expect that variations in breathing patterns change spectral markers in both the HF and LF bands of RR time series spectra. These changes exclusively due to the breathing pattern (i.e. the cause) should not be mistaken for abnormal changes in HRV (i.e. changes in the cause-to-effect relationship).

This paper shows that variations of the breathing frequency increase the LF/HF index. First, the theoretical spectrum of FM and low-pass filtered signals is presented in order to substantiate the working hypothesis. Next, spectral estimation methods of actual time series are briefly discussed in order to justify the spectral analysis method used here. Finally, simulation and experimental results are presented and discussed in order to draw some conclusions.

2. Theoretical spectrum of FM and low-pass filtered signals

The spectrum of a sine wave whose frequency is f_c and variance σ_c^2,

$$x_c(t) = \frac{\sigma_c}{\sqrt{2}} \cos(2\pi f_c t) \tag{1}$$

is a spectral peak located at f_c. If f_c varies with time, the signal spectrum changes. Consider for example the frequency modulated (FM) signal

$$x_{FM}(t) = \frac{\sigma_c}{\sqrt{2}} \cos\left(2\pi f_c t + 2\pi f_\Delta \int x_m(\lambda)\, d\lambda\right) \tag{2}$$

where f_Δ is the frequency deviation and $x_m(t)$ is the modulating signal with variance σ_m^2 and probability distribution function (PDF) $p_{x_m}(x)$. The quasi-static approximation (Peebles 1976) shows that the two-sided power spectrum of $x_{FM}(t)$ when the frequency of variation is slow compared to f_c is

$$S_{x_{FM}x_{FM}}(f) = \frac{\sigma_c^2\sigma_m^2}{2f_\Delta}\left[p_{x_m}\left(\frac{f-f_c}{f_\Delta}\right) + p_{x_m}\left(\frac{f+f_c}{f_\Delta}\right)\right]. \tag{3}$$

Therefore, frequency variation implies a broadening of the spectral peak, which depends on the PDF of the modulating signal.

Since there is a low-pass filtering action between breathing frequency and heart rate fluctuation (Womack 1971), we are interested in the spectrum of the output $y(t)$ of that filter, which is

$$S_y(f) = \frac{\sigma_c^2\sigma_m^2}{2f_\Delta}\left[p_{x_m}\left(\frac{f-f_c}{f_\Delta}\right) + p_{x_m}\left(\frac{f+f_c}{f_\Delta}\right)\right] |H_{LP}(f)|^2. \tag{4}$$

That is, the power spectrum of $y(t)$ is that of x_{FM} weighted by the filter transfer function. Hence, the low-frequency components of $x_{FM}(t)$ will be enhanced as compared to the high-frequency components.

3. Spectral estimation of RR time series

The spectral estimation of time series must consider the finite number of samples available and the sampling process itself. In an RR time series (tachogram), the information is provided by each QRS arrival, which results in non-uniform sampling, leading to spectral artifacts (Mateo and Laguna 2000). Resampling the tachogram with splines yields a uniformly sampled and interpolated RR time series, which avoids artifacts.

Spectral estimation methods can be either non-parametric, such as the periodogram and its modifications (Barlett, Welch and Blackman–Tukey periodograms), or parametric (AR, MA and ARMA modelling). The need for high-frequency resolution, the finite length of the time series, the smoothness of the spectra and its capability of identifying periodical components immersed in noise favoured the extended use of parametric estimation methods. Nevertheless, non-parametric methods are more accurate than parametric methods to quantify power distribution in frequency bands (Mateo and Laguna 2000), which is the basis for markers in HRV spectral analysis. Hence, we estimate the spectra from the periodogram (squared modulus of the FFT) of the tachogram resampled and interpolated by cubic splines.

Finally, frequency bands in HRV variability analysis must be delimited according to the intended application. Since the narrower the LF band, the smaller the LF/HF index, we normalize the LF/HF index to the signal bandwidth according to

$$\mathrm{LF/HF_n} = \frac{S_{\mathrm{LF}}}{S_{\mathrm{HF}}}\frac{\mathrm{BW_{HF}}}{\mathrm{BW_{LF}}}. \tag{5}$$

We are interested in variations in the $\mathrm{LF/HF_n}$ index because of variations in breathing frequency. Therefore, we will analyse RR time series during different breathing patterns that involve respiratory frequencies from 0.1 Hz to 0.2 Hz. Consequently, we define the three following frequency bands (see figure 1):

$$\begin{cases} f \leqslant 0.03\ \mathrm{Hz} & \text{VLF band} \\ 0.03\ \mathrm{Hz} < f \leqslant 0.09\ \mathrm{Hz} & \text{LF band} \\ 0.09\ \mathrm{Hz} < f < 0.4\ \mathrm{Hz} & \text{HF band.} \end{cases} \tag{6}$$

According to this definition, $\mathrm{BW_{LF}} = 0.06$ Hz and $\mathrm{BW_{HF}} = 0.31$ Hz.

4. Results from simulated tachograms

The first step in assessing how variations in respiratory frequency affect the $\mathrm{LF/HF_n}$ index is to analyse simulated tachograms that include different beat-to-beat interval modulations. A 5 min fragment of a periodic RR signal (in milliseconds) with $f_{\mathrm{c}} = 0.15$ Hz is

$$\mathrm{RR_p}(n) = 1000 + 100\cos(2\pi \times 0.15n) \qquad n \in [1, \ldots, 300] \tag{7}$$

where n is the heartbeat number. Hence, the shortest RR interval is 900 ms, the longest is 1100 ms and the average is 1000 ms. A 5 min fragment of an FM modulated RR signal (in milliseconds) with the same maximum, minimum and mean of $\mathrm{RR_p}$ and with $f_{\mathrm{c}} = 0.15$ Hz, $f_{\Delta} = 0.05$ Hz and $f_{\mathrm{m}} = 0.01$ Hz is

$$\mathrm{RR_{FM}}(n) = 1000 + 100\cos\left[2\pi \times 0.15n + 2\pi \times 0.05\sum_{i=1}^{n}\cos(2\pi \times 0.01\mathrm{i})\right]$$
$$n \in [1, \ldots, 300]. \tag{8}$$

Both tachograms are resampled at 4 Hz prior to the spectral estimation. Figure 1 shows that the respective frequency spectra are quite different in spite of the average breathing frequency

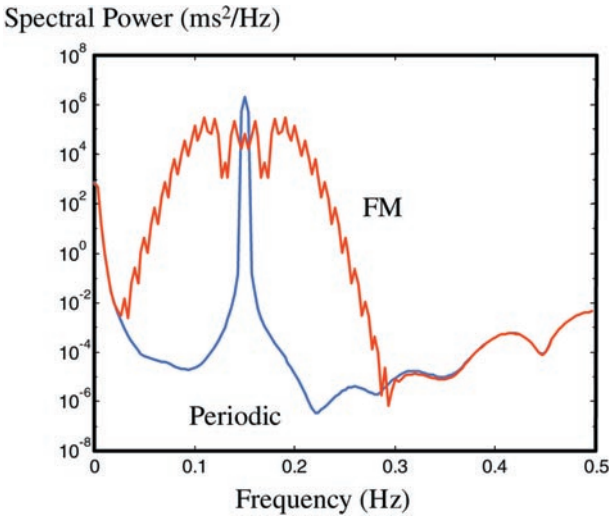

Figure 1. Spectra of simulated RR_{FM} and RR_p.

Table 1. Normalized power-spectra ratio index (LF/HF_n) for the RR time series under periodic (RR_p) and FM modulated (RR_{FM}) breathing after low-pass filtering with different cut-off frequencies.

	0.05 Hz	0.07 Hz	0.10 Hz	0.13 Hz	0.15 Hz	0.20 Hz
Periodic	796×10^{-6}	6.9×10^{-6}	0.7×10^{-6}	5.80×10^{-9}	2.07×10^{-9}	3.62×10^{-6}
FM	0.68	0.48	0.23	0.12	0.09	0.05

being the same (0.15 Hz). The LF/HF_n index is also very different: 0.03 for RR_{FM} and 7×10^{-9} for RR_p.

An improved simulation includes the low-pass filtering effect reported by Womack (1971). We have computed the LF/HF_n index for the outputs of several low-pass filters whose inputs were RR_p and RR_{FM}. The filters used were Butterworth fourth-order and bidirectional, with cutoff frequencies 0.05 Hz, 0.07 Hz, 0.10 Hz, 0.13 Hz, 0.15 Hz and 0.20 Hz. Table 1 shows the results. For the RR_{FM} signal, the lower the cut-off frequency, the higher the LF/HF_n index. For the RR_p signal, the cut-off frequency strongly affects the LF/HF_n index because of the small power in the LF band. In any case, the LF/HF_n index is always smaller for periodic RR signals than for FM RR signals.

Actual RR signals will be influenced by other heart rate variability factors in addition to the respiration. Therefore, in order to consider the spectral power in the LF band resulting only from the breathing pattern, we will high-pass filter the tachogram before performing spectral analysis. We have filtered the signals with a Butterworth fourth-order bidirectional high-pass filter with a cut-off frequency of 0.05 Hz. The results show that this filter has a negligible effect on the LF/HF_n index for the simulated signals.

5. Experimental results

We have recorded RR time series and breathing signals in 20 healthy subjects (30.9 ± 5.1 years) in supine position. Measurements for each subject induced five stages with well defined conditions. Each stage lasted for 5 minutes and was followed by a 2 minute resting interval.

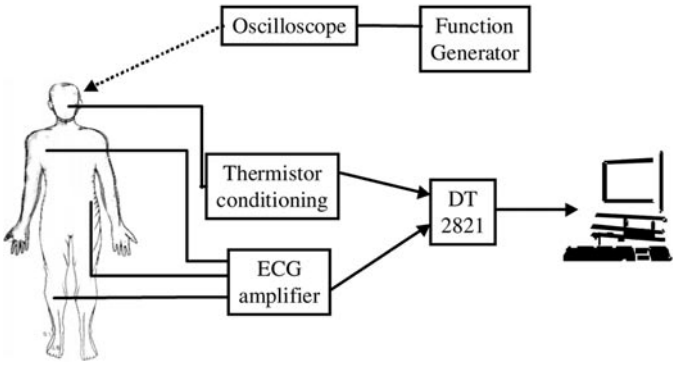

Figure 2. Measurement system.

Before starting, subjects were in supine position for 5 minutes. In the first stage, subjects breathed at will. In the second stage, subjects were asked to breathe periodically at 0.15 Hz by following a signal on an oscilloscope screen. In the third stage, subjects were asked to breathe according to an oscilloscope displaying a 0.15 Hz signal modulated in frequency by 0.01 Hz with a 0.05 Hz frequency deviation. In the fourth stage, subjects returned to periodical breathing at 0.15 Hz, and during the fifth stage, subjects breathed at will again.

Figure 2 shows the measurement setup. The isolated ECG amplifier (bandwidth 0.5 Hz to 500 Hz, gain 1000) recorded the standard II ECG lead. A nasal NTC thermistor yielded the breathing rhythm and amplitude. Since we were interested in the effects of breathing frequency, not amplitude, records whose amplitude were too different were discarded. ECG and breathing signals were sampled at 500 Hz in eight subjects and at 4 kHz in twelve subjects by a plug-in PC data-acquisition card (DT2821, Data Translation) and stored for further processing. RR time series were derived in two steps. The first step yielded an estimated location of each QRS complex by detecting when the ECG signal, low-pass filtered at 30 Hz and further differentiated, exceeded a threshold set at 75% of the maximal amplitude of the filtered signal. The second step corrected the estimated location by maximizing the correlation between the first QRS detected and the following ones. After properly detecting each QRS, the tachogram was computed by differentiating the position of each QRS. From the tachogram, a resampled RR time series was obtained with a sampling frequency of 4 Hz by interpolating with cubic splines. In order to remove low-frequency components present in the tachogram but unrelated to breathing patterns, the tachogram was high-pass filtered with a Butterworth fourth-order bidirectional filter with cut-off frequency at 0.05 Hz. Next, the periodogram was estimated for each subject and each stage, and the LF/HF_n was computed.

Figure 3 summarizes the results for the 20 subjects. Both sampling frequencies yielded the same results. The LF/HF_n index is largest when breathing freely and smallest when

Table 2. Significance of the differences between LF/HF_n for the different breathing stages. If $p < 0.05$, the difference is considered to be significant.

	Periodic 1	FM	Periodic 2	Free 2
Free 1	**0.0009**	**0.0254**	**0.0006**	0.1926
Periodic 1		**0.0014**	0.3390	**<0.0001**
FM			**0.0144**	**0.0003**
Periodic 2				**<0.0001**

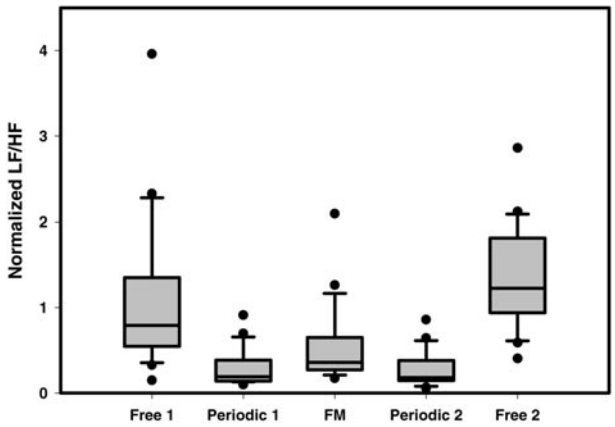

Figure 3. LF/HF_n index for the 20 subjects measured and the five stages (starting and finishing with breathing at will—'free'). Mean, standard deviation, fifth and 95th percentiles, and maximum and minimum are represented for each stage.

breathing periodically. FM breathing yields an intermediate index value. Differences between stages were tested by a paired Student *t*-test whose results are shown in table 2. There are no significant differences between the two stages of free breathing, nor between the two stages of periodic breathing. There are significant differences between free and periodic breathing between free and FM breathing and between periodic and FM breathing.

6. Discussion

The experimental results for periodic breathing show an LF/HF_n index smaller than that for FM breathing, the same as for the simulated data in figure 1 (signal RR_p). Nevertheless, the LF/HF_n index is larger for experimental than for simulated data. This is because the LF band of experimental data includes other modulations, such as those of the baroreceptor that are not completely rejected by the high-pass filter applied to the tachogram. It may also be due to drifts of the mean heart rhythm, to the non-sinusoidal waveform of the respiratory sinus arrhythmia and to changes in the transfer function between the breathing rhythm and the heart rate.

FM breathing yields a large LF/HF_n index as predicted from the theoretical analysis and from simulated data (RR_{FM}). Free breathing yields even larger values for the LF/HF_n index than FM breathing, which is consistent with the large variability in breathing patterns when subjects are allowed to breathe at will. Therefore, interpreting changes in the LF/HF_n index requires us to consider the breathing patterns simultaneous with the recorded RR series.

7. Conclusions

The respiratory sinus arrhythmia reflects the relationship between the autonomic nervous system and the cardiovascular system, but it also reflects the breathing pattern. Any variation in this pattern influences the RR time series and modifies its power spectrum. Periodic breathing yields low values for the LF/HF_n index. Breathing at will yields the larger LF/HF_n values. Therefore, comparisons between the LF/HF_n index for different subjects in HRV studies must consider the actual breathing pattern.

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